

NASA/CR-2002-211924
ICASE Report No. 2002-34



Linear Parameter Varying Control for Actuator Failure

Jong-Yeob Shin
ICASE, Hampton, Virginia

N. Eva Wu
Binghamton State University of New York, Binghamton, New York

Christine Belcastro
NASA Langley Research Center, Hampton, Virginia



DISTRIBUTION STATEMENT A
Approved for Public Release
Distribution Unlimited

October 2002

20021107 068

The NASA STI Program Office . . . in Profile

Since its founding, NASA has been dedicated to the advancement of aeronautics and space science. The NASA Scientific and Technical Information (STI) Program Office plays a key part in helping NASA maintain this important role.

The NASA STI Program Office is operated by Langley Research Center, the lead center for NASA's scientific and technical information. The NASA STI Program Office provides access to the NASA STI Database, the largest collection of aeronautical and space science STI in the world. The Program Office is also NASA's institutional mechanism for disseminating the results of its research and development activities. These results are published by NASA in the NASA STI Report Series, which includes the following report types:

- **TECHNICAL PUBLICATION.** Reports of completed research or a major significant phase of research that present the results of NASA programs and include extensive data or theoretical analysis. Includes compilations of significant scientific and technical data and information deemed to be of continuing reference value. NASA's counterpart of peer-reviewed formal professional papers, but having less stringent limitations on manuscript length and extent of graphic presentations.
- **TECHNICAL MEMORANDUM.** Scientific and technical findings that are preliminary or of specialized interest, e.g., quick release reports, working papers, and bibliographies that contain minimal annotation. Does not contain extensive analysis.
- **CONTRACTOR REPORT.** Scientific and technical findings by NASA-sponsored contractors and grantees.

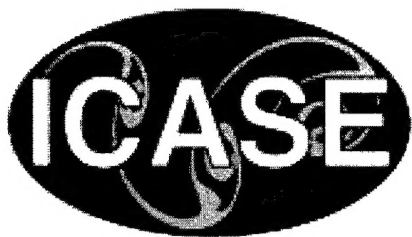
- **CONFERENCE PUBLICATIONS.** Collected papers from scientific and technical conferences, symposia, seminars, or other meetings sponsored or cosponsored by NASA.
- **SPECIAL PUBLICATION.** Scientific, technical, or historical information from NASA programs, projects, and missions, often concerned with subjects having substantial public interest.
- **TECHNICAL TRANSLATION.** English-language translations of foreign scientific and technical material pertinent to NASA's mission.

Specialized services that complement the STI Program Office's diverse offerings include creating custom thesauri, building customized data bases, organizing and publishing research results . . . even providing videos.

For more information about the NASA STI Program Office, see the following:

- Access the NASA STI Program Home Page at <http://www.sti.nasa.gov>
- Email your question via the Internet to help@sti.nasa.gov
- Fax your question to the NASA STI Help Desk at (301) 621-0134
- Telephone the NASA STI Help Desk at (301) 621-0390
- Write to:
NASA STI Help Desk
NASA Center for AeroSpace Information
7121 Standard Drive
Hanover, MD 21076-1320

NASA/CR-2002-211924
ICASE Report No. 2002-34



Linear Parameter Varying Control for Actuator Failure

Jong-Yeob Shin
ICASE, Hampton, Virginia

N. Eva Wu
Binghamton State University of New York, Binghamton, New York

Christine Belcastro
NASA Langley Research Center, Hampton, Virginia

ICASE
NASA Langley Research Center
Hampton, Virginia

Operated by Universities Space Research Association



Prepared for Langley Research Center
under Contract NAS1-97046

October 2002

Available from the following:

NASA Center for AeroSpace Information (CASI)
7121 Standard Drive
Hanover, MD 21076-1320
(301) 621-0390

National Technical Information Service (NTIS)
5285 Port Royal Road
Springfield, VA 22161-2171
(703) 487-4650

LINEAR PARAMETER VARYING CONTROL FOR ACTUATOR FAILURE

JONG-YEOB SHIN*, N. EVA WU†, AND CHRISTINE BELCASTRO‡

Abstract. A *robust* linear parameter varying (LPV) control synthesis is carried out for an HiMAT vehicle subject to loss of control effectiveness. The scheduling parameter is selected to be a function of the estimates of the control effectiveness factors. The estimates are provided on-line by a two-stage Kalman estimator. The inherent conservatism of the LPV design is reduced through the use of a scaling factor on the uncertainty block that represents the estimation errors of the effectiveness factors. Simulations of the controlled system with the on-line estimator show that a superior fault-tolerance can be achieved.

Key words. fault tolerant control system, fault parameter estimation, reconfigurable controller

Subject classification. Guidance and Control

1. Introduction. One of control schemes for a nonlinear system is a gain-scheduled linear parameter varying control technique [13, 1, 7, 16]. This approach is particularly appealing in that a nonlinear plant is treated as a linear parameter varying (LPV) system whose state-space matrices are functions of a scheduling parameter vector. This allows linear control techniques to be applied to a nonlinear system. Several researches on an LPV synthesis methodology allow the design of the global control law for an LPV system over a parameter set which is bounded and measurable [13, 1, 7, 16]. An LPV controller synthesis is formulated into a linear matrix inequality (LMI) optimization problem. There are LPV control synthesis methods according to a functional form of an LPV system. The polytopic LPV control synthesis method [2] is used for an LPV system which is a polytopic function of a scheduling parameter vector. The affine LPV control synthesis method [1] is applied to an affine LPV system, whose LMI constraints are evaluated at only vertex points of an LPV system. The grid LPV control synthesis method [7, 16] is for an LPV system which is a bounded function of a scheduling parameter vector. In the method, LMI constraints are evaluated at grid points over parameter spaces. These methods can be converted to each other by increasing conservatism to describe an LPV system. The grid LPV synthesis method has been successfully applied to synthesis controllers for the pitch-axis missile autopilots [17, 12], F-14 aircraft lateral-directional axis during powered approach [6, 4], turbofan engines [15, 5] and F-16 aircraft [14]. Scheduling parameters of these applications are physical parameters such as angle of attack, mach number, velocity, dynamic pressure, etc. Scheduling parameters in LPV control synthesis are required to be measurable and the variations of scheduling parameters should be in a bounded set.

In this paper, actuator failures are modeled as an LPV system as functions of actuator effectiveness parameters [9]. These parameters are estimated as biases using an augmented Kalman filter. A set of covariance-dependent forgetting factors is introduced into the filtering algorithm. As a result, the change in the actuator effectiveness is accentuated to help achieve a more accurate estimate more rapidly. The H_∞ bounds on parameter estimation errors are assessed through simulations, which are then used as bounds of real parameter uncertainty in the construction of a robust LPV control law. Actuator faults can be parameterized as estimated fault effectiveness parameters. Thus, it is possible to formulate a fault tolerance control design problem as an LPV control synthesis problem based on estimated faults parameters.

Fault estimation errors and modeling uncertainties are represented by an uncertainty block in the construction of a robust LPV control law. The structure of an uncertainty block is not included in a conventional LPV control synthesis methodology [7, 16]. A scaling factor on a uncertainty block can reduce conservatism of the LPV synthesis [1]. In Ref.[1], it is formulated into a single optimization problem to find a scaling factor and a control law to achieve a certain level of performance. The optimization problem is not a convex problem, which has unknown positive matrices X and Y related with a control law and a scaling factor S related with the uncertainty block structure. The problem is solved by an iteration method of fixing X and Y or a scaling factor S . In this paper, the problem is formulated into two LMI optimizations: one is to design

*ICASE, MS 132C, NASA Langley Research Center, Hampton, VA 23681. This research was supported by the National Aeronautics and Space Administration under NASA Contract No. NAS1-97046 while the first author was in residence at ICASE, NASA Langley Research Center, Hampton, VA 23681.

†Professor, Department of Electrical Engineering, Binghamton State University of New York, Binghamton, New York, 13902.

‡Researcher, Guidance Control Branch, NASA Langley Research Center, Hampton, VA 23681.

an LPV controller with given a scaling factor and the other is to determine a scaling factor S with a given control law. The problem is solved by an iteration method of fixing a control law instead of fixing variables X and Y . This helps to find a scaling factor S for minimizing an induced- \mathcal{L}_2 norm of the closed-loop system.

This paper contains the following sections. In Section 2, an LPV synthesis methodology used in this paper is summarized. In Section 3, fault parameter estimation methods are presented. In Section 4, an LPV controller for an aerospace vehicle is designed by using an LPV synthesis control methodology with a scaling factor. In Section 5, the simulation results of the closed-loop system are presented and this paper concludes with a brief summary in Section 6.

2. LPV Synthesis.

2.1. Problem Statements. In this section, a control synthesis problem is defined, based on an estimated parameter vector $\bar{p} \in \mathcal{R}^{n_s}$ such as actuator effectiveness [9]. Actuator effectiveness parameters represent actuator failure cases (actuator damage). Suppose actuator effectiveness parameter can be estimated using the estimation methods presented in Section 3. A system dynamics can be represented by an LPV system according to an estimated scheduling parameter vector and estimation error bounds.

An LPV system can be represented as functions of an estimated scheduling parameter vector \bar{p} with an uncertainty block Δ which captures parameter estimation errors and unmodeled dynamics. An LPV system can be written as:

$$\begin{bmatrix} \dot{x} \\ e_\Delta \\ e_p \\ y \end{bmatrix} = \begin{bmatrix} A(\bar{p}) & B_\Delta(\bar{p}) & B_p(\bar{p}) & B_u(\bar{p}) \\ C_e(\bar{p}) & D_{\Delta\Delta}(\bar{p}) & D_{\Delta p}(\bar{p}) & D_{\Delta u}(\bar{p}) \\ C_p(\bar{p}) & D_{p\Delta}(\bar{p}) & D_{pp}(\bar{p}) & D_{pu}(\bar{p}) \\ C_y(\bar{p}) & D_{y\Delta}(\bar{p}) & D_{yp}(\bar{p}) & 0 \end{bmatrix} \begin{bmatrix} x \\ d_\Delta \\ d_p \\ u \end{bmatrix}, d_\Delta = \Delta e_\Delta, \quad (2.1)$$

where $x \in \mathcal{R}^{n_x}$, $e_\Delta \in \mathcal{R}^{n_\Delta}$, $e_p \in \mathcal{R}^{n_{e_p}}$, $y \in \mathcal{R}^{n_y}$, $d_\Delta \in \mathcal{R}^{n_\Delta}$, $d_p \in \mathcal{R}^{n_{d_p}}$, and $u \in \mathcal{R}^{n_u}$. All of the state-space matrices are of appropriate dimensions.

An uncertainty block set Δ is defined as:

$$\Delta = \{\Delta = \text{diag}(\delta_1 I_1, \dots, \delta_n I_n, \Delta_{n+1}, \dots, \Delta_{n+m}) : \delta_i \in R, \Delta_i \in R^{l \times l}, \bar{\sigma}(\Delta) \leq \beta\}, \quad (2.2)$$

where β is normalized to 1 without loss of generality. There exists a scaling factor set S such that

$$S = \{S : S > 0, S\Delta = \Delta S, S \in \mathcal{R}^{n_\Delta \times n_\Delta}\}. \quad (2.3)$$

The input/output scaling matrices $L^{-1/2}$ and $J^{1/2}$ are defined as

$$L^{-1/2} = \begin{bmatrix} S^{-1/2} & 0 \\ 0 & I_{n_{d_p}} \end{bmatrix} \in \mathcal{R}^{(n_\Delta + n_{d_p}) \times (n_\Delta + n_{d_p})}, \quad J^{1/2} = \begin{bmatrix} S^{1/2} & 0 \\ 0 & I_{n_{e_p}} \end{bmatrix} \in \mathcal{R}^{(n_\Delta + n_{e_p}) \times (n_\Delta + n_{e_p})}, \quad (2.4)$$

where $S^{1/2} \in S$ and $S^{-1/2} \in S$.

The induced \mathcal{L}_2 -norm of a parameter dependent stable LPV system is defined as

$$\|G\|_{2 \leftarrow 2} \equiv \sup_{\forall \bar{p}, d \in \mathcal{L}_2, d \neq 0} \frac{\|e\|_2}{\|d\|_2},$$

for zero initial conditions $x(0) = 0$.

Suppose there exists an LPV controller $K(\bar{p})$ which stabilizes an LPV system $P(\bar{p})$. The control synthesis problem is:

$$\min_{K(\bar{p}), S \in S} \|J^{1/2}(S)F_l(P(\bar{p}), K(\bar{p}))L^{-1/2}(S)\|_{2 \leftarrow 2}, \quad (2.5)$$

where $F_l(P(\bar{p}), K(\bar{p}))$ means a lower linear fraction transformation (LFT). The optimization problem of equation (2.5) is not convex in $K(\bar{p})$ and S . The problem is similar to a D-K iteration. In this paper, we approach to the problem in a similar manner of solving the D-K iteration problem[3].

2.2. Control Synthesis Methodology. In this section, a procedure of solving the problem is presented. There is an LPV control synthesis methodology in Ref. [1] with a scaling factor. In Ref. [1], an LMI optimization can be formulated with unknown matrices $X > 0$, $Y > 0$, and scaling factor matrices $J^{1/2}$ and $L^{-1/2}$. However, an LMI optimization problem in Ref. [1] has an equality constraint. In this paper, to avoid an equality constraint, the augmented LPV system with the scaling matrices $J^{1/2}$ and $L^{-1/2}$ is used to design an LPV controller.

Suppose a scaling factor S is given. The augmented LPV open-loop system with the scaling matrices $J^{1/2}$ and $L^{-1/2}$ can be written as:

$$\begin{bmatrix} \dot{x} \\ e \\ y \end{bmatrix} = \begin{bmatrix} A(\bar{\rho}) & \bar{B}_1(\bar{\rho}) & B_2(\bar{\rho}) \\ \bar{C}_1(\bar{\rho}) & \bar{D}_{11}(\bar{\rho}) & \bar{D}_{12}(\bar{\rho}) \\ C_2(\bar{\rho}) & \bar{D}_{21}(\bar{\rho}) & 0 \end{bmatrix} \begin{bmatrix} x \\ d \\ u \end{bmatrix} \equiv \begin{bmatrix} A(\bar{\rho}) & B_1(\bar{\rho})L^{-1/2} & B_2(\bar{\rho}) \\ J^{1/2}C_1(\bar{\rho}) & J^{1/2}D_{11}(\bar{\rho})L^{-1/2} & J^{1/2}D_{12}(\bar{\rho}) \\ C_2(\bar{\rho}) & D_{21}(\bar{\rho})L^{-1/2} & 0 \end{bmatrix} \begin{bmatrix} x \\ d \\ u \end{bmatrix} \quad (2.6)$$

where $e = [e_\Delta^T \ e_p^T]^T$ and $d = [d_\Delta^T \ d_p^T]^T$. With assumption that $\bar{D}_{12}(\bar{\rho})$ and $\bar{D}_{21}(\bar{\rho})$ are full column and row rank for all $\bar{\rho}$, respectively, an LPV control synthesis methodology in Ref. [16, 7] can be used in this paper. For the sake of completeness, a brief summary of the LPV control synthesis methodology in Ref. [16] is presented in this section.

Using Q-R decompositions[7] of matrices $\bar{D}_{12}(\bar{\rho})$ and $\bar{D}_{21}(\bar{\rho})$, the augmented LPV system is rewritten as:

$$\begin{bmatrix} \dot{x} \\ e_1 \\ e_2 \\ y \end{bmatrix} = \begin{bmatrix} A(\bar{\rho}) & B_{11}(\bar{\rho}) & B_{12}(\bar{\rho}) & B_2(\bar{\rho}) \\ C_{11}(\bar{\rho}) & D_{1111}(\bar{\rho}) & D_{1112}(\bar{\rho}) & 0 \\ C_{12}(\bar{\rho}) & D_{1121}(\bar{\rho}) & D_{1122}(\bar{\rho}) & I_{n_{e_2}} \\ C_2(\bar{\rho}) & 0 & I_{n_{d_2}} & 0 \end{bmatrix} \begin{bmatrix} x \\ d_1 \\ d_2 \\ u \end{bmatrix}, \quad (2.7)$$

where $d_1 \in \mathcal{R}^{n_{d_1}}$, $d_2 \in \mathcal{R}^{n_{d_2}}$, $e_1 \in \mathcal{R}^{n_{e_1}}$, and $e_2 \in \mathcal{R}^{n_{e_2}}$. Matrices D_{1111} , D_{1112} , D_{1121} , D_{1122} , C_{11} , C_{12} are of appropriate dimensions.

There exists an LPV controller $K(\bar{\rho})$ which leads to the induced- \mathcal{L}_2 norm of the closed-loop system being less than constant γ . The LPV controller $K(\bar{\rho})$ can be constructed from the solution matrices, $X(\bar{\rho}) \in \mathcal{R}^{n \times n}$ and $Y(\bar{\rho}) \in \mathcal{R}^{n \times n}$ which are calculated by solving the following LMI optimization.

$$\min_{X(\bar{\rho}), Y(\bar{\rho})} \gamma, \quad (2.8)$$

subject to

$$\begin{bmatrix} X(\bar{\rho})\hat{A}^T(\bar{\rho}) + \hat{A}(\bar{\rho})X(\bar{\rho}) + \sum_{i=1}^m (\bar{\nu}_i \frac{\partial X}{\partial \bar{\rho}_i}) - B_2(\bar{\rho})B_2^T(\bar{\rho}) & X(\bar{\rho})C_{11}^T(\bar{\rho}) & \gamma^{-1}\hat{B}(\bar{\rho}) \\ C_{11}(\bar{\rho})X(\bar{\rho}) & -I_{n_{e_1}} & \gamma^{-1}D_{111.1}(\bar{\rho}) \\ \gamma^{-1}\hat{B}^T(\bar{\rho}) & \gamma^{-1}D_{111.1}^T(\bar{\rho}) & -I_{n_d} \end{bmatrix} < 0, \quad (2.9)$$

$$\begin{bmatrix} \tilde{A}(\bar{\rho})Y(\bar{\rho}) + Y(\bar{\rho})\tilde{A}^T(\bar{\rho}) + \sum_{i=1}^m (\bar{\nu}_i \frac{\partial Y}{\partial \bar{\rho}_i}) - C_2^T(\bar{\rho})C_2(\bar{\rho}) & Y(\bar{\rho})B_{11}(\bar{\rho}) & \gamma^{-1}\tilde{C}^T(\bar{\rho}) \\ B_{11}^T(\bar{\rho})Y(\bar{\rho}) & -I_{n_{d_1}} & \gamma^{-1}D_{11.1}^T(\bar{\rho}) \\ \gamma^{-1}\tilde{C}(\bar{\rho}) & \gamma^{-1}D_{11.1}(\bar{\rho}) & -I_{n_e} \end{bmatrix} < 0, \quad (2.10)$$

$$\begin{bmatrix} X(\bar{\rho}) & \gamma^{-1}I_n \\ \gamma^{-1}I_n & Y(\bar{\rho}) \end{bmatrix} \geq 0, \quad (2.11)$$

$$X(\bar{\rho}) > 0, \ Y(\bar{\rho}) > 0,$$

where

$$\hat{A}(\bar{\rho}) \equiv A(\bar{\rho}) - B_2(\bar{\rho})C_{12}(\bar{\rho}), \ \hat{B}(\bar{\rho}) \equiv B_1(\bar{\rho}) - B_2(\bar{\rho})D_{112.1}(\bar{\rho}), \quad (2.12)$$

$$\tilde{A}(\bar{\rho}) \equiv A(\bar{\rho}) - B_{12}(\bar{\rho})C_2(\bar{\rho}), \ \tilde{C}(\bar{\rho}) \equiv C_1(\bar{\rho}) - D_{11.2}(\bar{\rho})C_2(\bar{\rho}). \quad (2.13)$$

The definitions of matrices D_{112} , D_{111} , D_{111} , and D_{112} are taken from Ref. [16]. Also, the realization of an LPV controller from the solution matrices X and Y are taken from Ref. [16].

The benefit of the LPV synthesis methodology is that there is no limitation of an affine functional form of LPV system state-space matrices. Since the LMI constraints in equations (2.9)-(2.10) are evaluated at grid points over all scheduling parameter spaces, an LPV system should be just a function of a scheduling parameter. In this paper, we consider actuators are failed one at a time. In the failure case, the system variations due to actuator failures can not be represented by an affine function of an actuator failure parameter vector. The disadvantage of the LPV control synthesis methodology is that robust stability over all parameter spaces is not guaranteed unless choosing appropriate number of grid points.

Suppose there exists an designed LPV controller $K(\bar{\rho})$ which stabilizes the augmented LPV system. The closed-loop LPV system with a given controller is written as:

$$\begin{bmatrix} \dot{x}_{cl} \\ e_{\Delta} \\ e_p \end{bmatrix} = \begin{bmatrix} A_{cl}(\rho) & B_{1_{cl}}(\rho)S^{-1/2} & B_{2_{cl}}(\rho) \\ S^{1/2}C_{1_{cl}}(\rho) & S^{1/2}D_{11_{cl}}(\rho)S^{-1/2} & S^{1/2}D_{21_{cl}}(\rho) \\ C_{2_{cl}}(\rho) & D_{21_{cl}}(\rho)S^{-1/2} & D_{22_{cl}}(\rho) \end{bmatrix} \begin{bmatrix} x_{cl} \\ d_{\Delta} \\ d_p \end{bmatrix}, \quad d_{\Delta} = \Delta e_{\Delta}, \quad (2.14)$$

where $x_{cl} = [x^T \ x_k^T]^T$.

Applying the Kalman-Yakubovich-Popov (KYP) Lemma [9], the LMI optimization is formulated to find a scaling factor S . There exists an scaling factor $S \in \mathcal{S}$ which leads to the induced- \mathcal{L}_2 norm of the closed-loop system being less than γ_s . The scaling factor S can be determined solving the following LMI optimization.

$$\min_{P>0, S \in \mathcal{S}} \gamma_s, \quad (2.15)$$

$$\begin{bmatrix} M_{11} & PB_{1_{cl}} + \gamma_s^{-1}C_{2_{cl}}^T D_{21_{cl}} + C_{1_{cl}}^T S D_{11_{cl}} & PB_{2_{cl}} + \gamma_s^{-1}C_{2_{cl}}^T D_{22_{cl}} + C_{1_{cl}}^T S D_{12_{cl}} \\ \star & \gamma_s^{-1}D_{21_{cl}}^T D_{21_{cl}} + D_{11_{cl}}^T S D_{11_{cl}} - S & \gamma_s^{-1}D_{21_{cl}}^T D_{22_{cl}} + D_{11_{cl}}^T S D_{12_{cl}} \\ \star & \star & \gamma_s^{-1}D_{22_{cl}}^T D_{22_{cl}} + D_{12_{cl}}^T S D_{12_{cl}} - I \end{bmatrix} < 0 \quad (2.16)$$

where

$$M_{11} = A^T P + P A + \dot{P} + \gamma_s^{-1}C_{2_{cl}}^T C_{2_{cl}} + C_{1_{cl}}^T S C_{1_{cl}}.$$

In the LMI constraint, \star denotes a symmetric component.

The iteration procedure to solve the problem in equation (2.5) is follows:

1. Design an LPV controller $K(\bar{\rho})$ for a system from the LMI optimization in equation (2.8) with fixed S . At the first iteration, S is assumed as I .
2. Solve the LMI optimization problem in equation (2.15) over $P(\bar{\rho})$ and S based on the closed-loop system with the designed LPV controller $K(\bar{\rho})$.
3. Generate an augmented LPV system with the scaling factor S

$$G_{i+1}(\bar{\rho}) = \begin{bmatrix} S^{1/2} & 0 \\ 0 & I \end{bmatrix} G_i(\bar{\rho}) \begin{bmatrix} S^{-1/2} & 0 \\ 0 & I \end{bmatrix}, \quad (2.17)$$

where $G_i(\bar{\rho})$ is an LPV model at the i^{th} iteration.

4. Iterate over step 1 to 3 until convergence or terminate iteration based on satisfaction with a designed LPV controller.

The iteration method can not guarantee finding global solutions of K and S since the problem in equation (2.5) is not convex in K and S . Also, there is no guarantee of convergence in the iteration process. In the LPV synthesis methodology, the matrix $P(\bar{\rho})$ is related with the solution matrices X and Y of equations (2.9)-(2.10). When a designed controller is fixed to calculate the scaling factor S , the matrix $P(\bar{\rho})$ can be calculated from the solution matrices X and Y and fixed in the LMI optimization [16]. In this paper, the matrix $P(\bar{\rho})$ is also set as an unknown matrix in the LMI optimization in equation (2.15) to relax the constraints of fixing the LPV controller $K(\bar{\rho})$. Thus, there are two LMI optimizations in the iteration process.

3. Parameter Estimation. This section briefly describes the formulation of a real parameter estimation problem, which, when specialized to the actuator effectiveness estimation, transforms a fault (loss of actuator effectiveness) tolerant control problem to a robust LPV control problem. The development of this section follows that in Ref. [9].

The estimator is based on a linear discrete design model of the form:

$$x_{k+1} = A_k^d x_k + [b_1^d \gamma_k^1 \cdots b_{n_u}^d \gamma_k^{n_u}] \begin{bmatrix} u_k^1 \\ u_k^2 \\ \vdots \\ u_k^{n_u} \end{bmatrix} + B_k^d u_k + w_k^x \quad (3.1)$$

$$= A_k^d x_k + E_k^d \gamma_k + B_k^d u_k + w_k^x, \quad (3.2)$$

$$\gamma_{k+1} = \gamma_k + w_k^\gamma, \quad (3.3)$$

$$y_k = C_k^d x_k + v_k, \quad (3.4)$$

where $x_k \in R^{n_x}$, $\gamma_k \in R^{n_\gamma}$, $u_k \in R^{n_u}$ and $y_k \in R^{n_y}$ are the state, bias, input, and output variables, respectively. The discrete model can be obtained from a continuous model via, for example, the Euler's rule with a sampling period T_s , which preserves the functional dependence of the "B" matrix on γ . The bias vector γ with component $-1 \leq \gamma_k^i \leq 0$ relates to a actuator failure parameter. It is obvious that $E_k^d = B_k^d \times \text{diag}\{u_k^1, \dots, u_k^{n_u}\}$. w_k^x , w_k^γ and v_k denote the white noise sequences of uncorrelated Gaussian random vectors with zero means and covariance matrices Q_k^x , Q_k^γ and R_k , respectively.

The minimum variance solution is obtained by a direct application of the two-stage Kalman filter algorithm of Keller and Darouach[8], with constant coefficient matrices in Ref. [8] replaced by time-varying matrices. The filter is decoupled into four sets of equations. They given as follows.

—Optimal bias estimator

$$\begin{aligned} \hat{\gamma}_{k+1|k} &= \hat{\gamma}_{k|k}, \\ P_{k+1|k}^\gamma &= P_{k|k}^\gamma + Q_k^\gamma, \\ \hat{\gamma}_{k+1|k+1} &= \hat{\gamma}_{k+1|k} + K_{k+1}^\gamma (\tilde{r}_{k+1} - H_{k+1|k} \hat{\gamma}_{k|k}), \\ K_{k+1}^\gamma &= P_{k+1|k}^\gamma H_{k+1|k}^T \\ &\quad (H_{k+1|k} P_{k+1|k}^\gamma H_{k+1|k}^T + \tilde{S}_{k+1})^{-1}, \\ P_{k+1|k+1}^\gamma &= (I - K_{k+1}^\gamma H_{k+1|k}) P_{k+1|k}^\gamma. \end{aligned}$$

—Bias-free state estimator

$$\begin{aligned} \tilde{x}_{k+1|k} &= A_k^d \tilde{x}_{k|k} + B_k^d u_k + W_k \hat{\gamma}_{k|k} - V_{k+1|k} \hat{\gamma}_{k|k}, \\ \tilde{P}_{k+1|k}^x &= A_k^d \tilde{P}_{k|k}^x (A_k^d)^T + Q_k^x + W_k P_{k|k}^\gamma W_k^T \\ &\quad - V_{k+1|k} P_{k+1|k}^\gamma V_{k+1|k}^T, \\ \tilde{x}_{k+1|k+1} &= \tilde{x}_{k+1|k} + \tilde{K}_{k+1}^x (y_{k+1} - C_{k+1}^d \tilde{x}_{k+1|k}), \\ \tilde{K}_{k+1}^x &= \tilde{P}_{k+1|k}^x (C_{k+1}^d)^T \{C_{k+1}^d \tilde{P}_{k+1|k}^x (C_{k+1}^d)^T \\ &\quad + R_{k+1}\}^{-1}, \\ \tilde{P}_{k+1|k+1}^x &= (I - \tilde{K}_{k+1}^x C_{k+1}^d) \tilde{P}_{k+1|k}^x, \end{aligned}$$

where the filter residual and its covariance are given as

$$\begin{aligned} \tilde{r}_{k+1} &= y_{k+1} - C_{k+1}^d \tilde{x}_{k+1|k}, \\ \tilde{S}_{k+1} &= C_{k+1}^d \tilde{P}_{k+1|k}^x (C_{k+1}^d)^T + R_{k+1}. \end{aligned}$$

—Coupling equations

$$\begin{aligned} W_k &= A_k^d V_{k|k} + E_k^d, \\ V_{k+1|k} &= W_k P_{k|k}^\gamma (P_{k+1|k}^\gamma)^{-1}, \\ H_{k+1|k} &= C_{k+1}^d V_{k+1|k}, \\ V_{k+1|k+1} &= V_{k+1|k} - \tilde{K}_{k+1}^x H_{k+1|k}. \end{aligned}$$

—And finally the compensated state and error covariance estimates

$$\begin{aligned} \hat{x}_{k+1|k+1} &= \tilde{x}_{k+1|k+1} + V_{k+1|k+1} \hat{\gamma}_{k+1|k+1}, \\ P_{k+1|k+1} &= \tilde{P}_{k+1|k+1}^x + V_{k+1|k+1} P_{k+1|k+1}^\gamma V_{k+1|k+1}^T. \end{aligned}$$

A further measure is taken to modify the above filtering algorithm so that the estimates become more responsive to abrupt changes in the control effectiveness factors.

A well known technique for estimating time-varying parameters is the use of forgetting factors. The basic idea is to enable a recursive algorithm to discount the past information so that the filter is more apt to recognize the changes in the system. Since the time update of the bias estimate governed by $\hat{\gamma}_{k+1|k} = \hat{\gamma}_{k|k}$ is the dominant opposing force to acknowledge the abrupt changes in the biases, forgetting factors introduced into the time propagation equation $P_{k+1|k}^\gamma = P_{k|k}^\gamma + Q_k^\gamma$ of the bias covariance is likely to function most effectively.

Assume that covariance $P_{k|k}^\gamma$ adequately describes the bias estimation error along both temporal and spacial directions under the normal system operation condition. Then this covariance provides a basis for the selection of forgetting factors. The bias estimates should be prevented from being impetuous, as well as from being indifferent to the changes shown in the measurements. A technique suggested in Ref. [11] amounts to select forgetting factors that would force the adjusted covariance in $P_{k+1|k}^\gamma = P_{k|k}^\gamma + Q_k^\gamma$ to stay within some prescribed bounds

$$\sigma_{\min} I \leq P_{k+1|k}^\gamma \leq \sigma_{\max} I, \quad (3.5)$$

where σ_{\min} and σ_{\max} are positive constants with $0 < \sigma_{\min} < \sigma_{\max} < \infty$, and I is the identity matrix. Let the dyadic expansion of $P_{k|k}^\gamma$ be given by

$$P_{k|k}^\gamma = \sum_{i=1}^{n_u} \alpha_{k|k}^i e_k^i (e_k^i)^T, \quad (3.6)$$

where $\alpha_{k|k}^1, \dots, \alpha_{k|k}^{n_u}$ are the eigenvalues of $P_{k|k}^\gamma$ with $\alpha_{k|k}^1 \geq \dots \geq \alpha_{k|k}^{n_u}$, and $e_k^1, \dots, e_k^{n_u}$ are the corresponding eigenvectors with $\|e_k^1\| = \dots = \|e_k^{n_u}\| = 1$. Equation (3.6) can then be expressed as

$$P_{k+1|k}^\gamma = \sum_{i=1}^{n_u} \frac{\alpha_{k|k}^i}{\lambda_k^i} e_k^i (e_k^i)^T + Q_k^\gamma, \quad 0 < \lambda_k^i \leq 1.$$

Following the argument in Ref. [11], the forgetting factor λ_k^i can be chosen as a decreasing function of the amount of information received in the direction e_k^i . Since eigenvalue $\alpha_{k|k}^i$ of $P_{k|k}^\gamma$ is a measure of the uncertainty in the direction of e_k^i , a choice of forgetting factor λ_k^i based on the above constraints can be

$$\lambda_k^i = \begin{cases} \lambda_o, & \alpha_{k|k}^i > \alpha_{\max}, \\ \alpha_{k|k}^i \left[\alpha_{\min} + \frac{\alpha_{\max} - \alpha_{\min}}{\alpha_{\max}} \alpha_{k|k}^i \right]^{-1}, & \alpha_{k|k}^i \leq \alpha_{\max}. \end{cases} \quad (3.7)$$

The estimation algorithm discussed in this section will be seen to have been applied successfully to a HiMAT vehicle.

4. Example. In this section, the iteration process described in Section 2.2 is applied to control a HiMAT vehicle for actuator failure cases. Recall it is assumed that actuators are failed one at a time. Thus, the control reconfigurability of the HiMAT vehicle never goes to zero [10]. The system variations due to actuator failures can be modeled as an LPV system, a function of an estimated scheduling parameter.

4.1. Linear Parameter Varying Model of HiMAT. The model of the HiMAT vehicle taken from the μ -synthesis Toolbox [3] has two inputs: elevons δ_e and canards δ_c ; two outputs: angle of attack α in radians and pitch angle θ in radians; and four states: velocity V in ft/sec, angle of attack, pitch rate q in rad/sec, and pitch angle. The open-loop model is

$$\begin{bmatrix} \dot{x} \\ y \end{bmatrix} = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{bmatrix} x \\ u \end{bmatrix}, \quad u = \begin{bmatrix} \delta_e \\ \delta_c \end{bmatrix}, \quad (4.1)$$

where

$$A = \begin{bmatrix} -0.0226 & -36.6 & -18.9 & -32.1 \\ 0 & -1.9 & 0.98 & 0 \\ 0.012 & -11.7 & -2.63 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}, B = \begin{bmatrix} 0 & 0 \\ -0.414 & 0 \\ -77.8 & 22.4 \\ 0 & 0 \end{bmatrix}, C = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, D = 0_{2 \times 2}. \quad (4.2)$$

A failure parameter vector $\tau = [\tau_1 \ \tau_2]^T$ is determined by the two actuator effectiveness parameters τ_1 and τ_2 of elevon and canard actuators, respectively. Assume that the failure parameters linearly enter in the model. The state-space model of the HiMAT vehicle is written as

$$\dot{x} = Ax + B(\tau)u, \quad y = Cx,$$

where A and C are constant matrices and $B(\tau) = [b_1\tau_1 \ b_2\tau_2]$. The vectors b_1 and b_2 are the columns of B . The actuator failure parameters can be estimated using the estimation method described in Section 3. However, there is estimation error $\delta_\tau = [\delta_{\tau_1} \ \delta_{\tau_2}]^T$. The actuator failure parameter vector τ is written as

$$\tau = \bar{\tau} + \delta_\tau,$$

where $\bar{\tau}$ is an estimated value. The estimation error bound is assumed as $\sqrt{\delta_\tau^T \delta_\tau} \leq 0.05$ for each actuator failure case. The matrix $B(\tau)$ is rewritten as:

$$B(\tau) = B \begin{bmatrix} \bar{\tau}_1 + 0.05\delta_1 & 0 \\ 0 & \bar{\tau}_2 + 0.05\delta_2 \end{bmatrix}, \quad (4.3)$$

where the real uncertainty parameters δ_1 and δ_2 vary from -1 to 1, respectively.

The LPV model of HiMAT is

$$\dot{x} = Ax + B \begin{bmatrix} \bar{\tau}_1 & 0 \\ 0 & \bar{\tau}_2 \end{bmatrix} u + B \begin{bmatrix} 0.05 & 0 \\ 0 & 0.05 \end{bmatrix} w, \quad (4.4)$$

$$z = u, \quad y = Cx, \quad (4.5)$$

$$w = \Delta z, \quad \Delta = \begin{bmatrix} \delta_1 & 0 \\ 0 & \delta_2 \end{bmatrix}. \quad (4.6)$$

The LPV model in equation (4.4) is a linear function of a parameter vector τ . However, the parameter vector τ can not be chosen as a scheduling parameter since we consider that the actuators are failed one at a time. Thus, τ_1 and τ_2 can not be zero simultaneously. To describe the failure cases, a synthetic scheduling parameter $\bar{\rho}$ is introduced as $0 \leq \bar{\rho} \leq 2$.

$$\begin{aligned} 0 \leq \bar{\rho} < 1 & : & 0 \leq \bar{\tau}_1 < 1, & \bar{\tau}_2 = 1 \\ \bar{\rho} = 1 & : & \bar{\tau}_1 = 1, & \bar{\tau}_2 = 1 \\ 1 < \bar{\rho} \leq 2 & : & \bar{\tau}_1 = 1, & 0 \leq \bar{\tau}_2 < 1 \end{aligned} \quad (4.7)$$

Note that the LPV model of the HiMAT vehicle is not an affine function of a scheduling parameter $\bar{\rho}$.

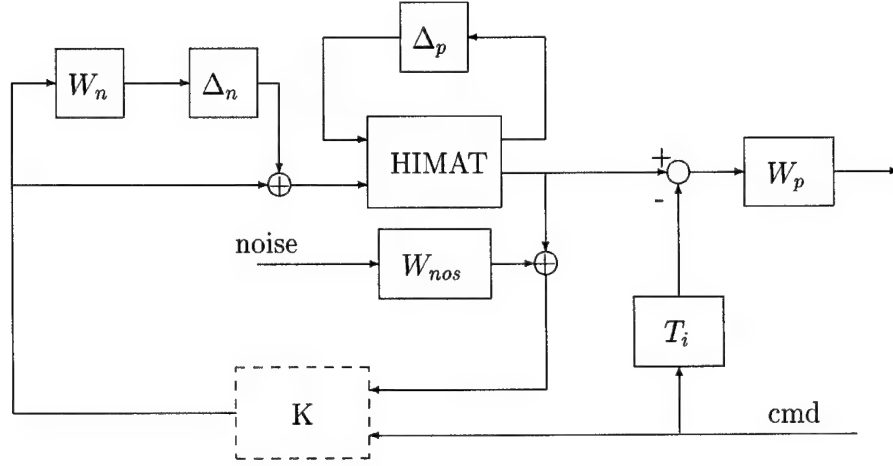


FIG. 4.1. Interconnection structure for the model matching problem.

4.2. LPV Controller Design. The control objective is to track a pitch angle command at actuator failure cases. A designed LPV controller should robustly stabilize the HiMAT vehicle over the failure parameter variations. The controller synthesis problem is formulated as a model matching problem in Figure 4.1.

The ideal response model T_i of pitch angle is taken from the example in the μ -synthesis Toolbox [3]. The performance weighting function W_p and unmodeled dynamics W_n are also taken from the example in the μ -synthesis Toolbox [3]. The sensor noise is modeled as white noise with 0.6° amplitude for angle of attack and pitch angle measurements. The weighting functions in Figure 4.1 are

$$\begin{aligned} T_i &= \frac{1}{s/0.8 + 1}, \\ W_p &= 40 \frac{s/50 + 1}{s/0.05 + 1}, \\ W_n &= 0.2 \frac{s/5 + 1}{s/1000 + 1} I_{2 \times 2}, \\ W_{nos} &= 0.01 I_{2 \times 2}. \end{aligned}$$

The control synthesis problem of the HiMAT vehicle is formulated to minimize the induced- \mathcal{L}_2 norm of the augmented LPV system with the weighting functions.

To solve the control synthesis LMI optimization problem in equation (2.8), basis functions for $X(\bar{\rho})$ and $Y(\bar{\rho})$ are required since X and Y are assumed as functions of $\bar{\rho}$.

$$X(\bar{\rho}) = \sum_i f_i(\bar{\rho}) X_i, \quad X_i \in \mathcal{R}^{n \times n}, \quad Y(\bar{\rho}) = \sum_j g_j(\bar{\rho}) Y_j, \quad Y_j \in \mathcal{R}^{n \times n}. \quad (4.8)$$

where basis functions $f_i(\bar{\rho})$ and $g_j(\bar{\rho})$ are given before solving the LMI optimization in equation (2.8) over X_i and Y_j . There is no analytic method to choose optimal basis functions for X and Y in general. The functions $f_i(\bar{\rho})$ and $g_j(\bar{\rho})$ are related with sensitivity of unknown matrices X_i and Y_i , respectively. In this paper, the basis function set is defined as $\{1, 1/\bar{\rho}, \bar{\rho}\}$ for X and Y to help the LMI optimization for total failure cases ($\bar{\tau}_1 = 0, \bar{\tau}_2 = 0$). Note that it is not necessary to define that $g_j(\bar{\rho})$ is equal to $f_i(\bar{\rho})$. Since X and Y are functions of $\bar{\rho}$, the parameter rate bound is required to solve the LMI optimization in equation (2.8). Recall that the scheduling parameter is an actuator failure parameter. Thus, for example, the scheduling parameter can suddenly vary from 1 (no failure case) to 2 (total canard failure case). In this paper, the parameter rate bound is assumed as $|\dot{\bar{\rho}}| < 100$ to capture sudden variations of the scheduling parameter.

To make the LMI optimization computationally tractable, the LMI constraints are evaluated at the following grid points:

$$\bar{\rho} \in \{\bar{\rho}|0.01, 0.1, 0.2, \dots, 1.9, 2\}.$$

TABLE 4.1
 γ values in the LMI optimization in equation (2.8)

Iteration	γ	S
1	1.23	$\text{diag}([1,1,1,1])$
2	0.71	$\text{diag}([0.497, 0.168, 1.186, 1.277])$
3	0.60	$\text{diag}([1.404, 1.289, 1.801, 1.453])$
4	0.54	$\text{diag}([1.580, 2.193, 2.100, 1.187])$
5	0.85	$\text{diag}([2.007, 1.430, 2.506, 1.849])$

Also, the same grid points are used to solve the LMI optimization in equation (2.15). To solve the LMI optimization in equation (2.15), the basis function set for P is required. Since the matrix P is related with X and Y , the basis function set for P is chosen as $\{1, 1/\bar{\rho}, \bar{\rho}\}$.

In this paper, the scaling factor S is assumed as constant over all scheduling parameter variations. The γ values and the scaling factor S for each iteration are written in Table 4.2. The scaling factor S is associated with the uncertainty block Δ which is

$$\Delta = \text{diag}([\delta_1, \delta_2, \delta_{ele}, \delta_{can}]).$$

Recall that the real uncertainty parameters δ_1 and δ_2 are associated with elevon and canard actuator failure parameters, respectively. The multiplicative uncertainty parameters δ_{ele} and δ_{can} are also associated with elevon and canard control channels in Figure 4.1.

The iteration process is stopped at the 5th iteration since the γ value at the iteration is greater than the previous iteration. Recall that the iteration process is not guaranteed to be converged. However, the performance index γ in the LMI optimization of equation (2.8) is significantly reduced from 1.23 to 0.54 by using the scaling factor S . In the remainder of this paper, the LPV controller for the HiMAT vehicle denotes the designed LPV controller at the 4th iteration.

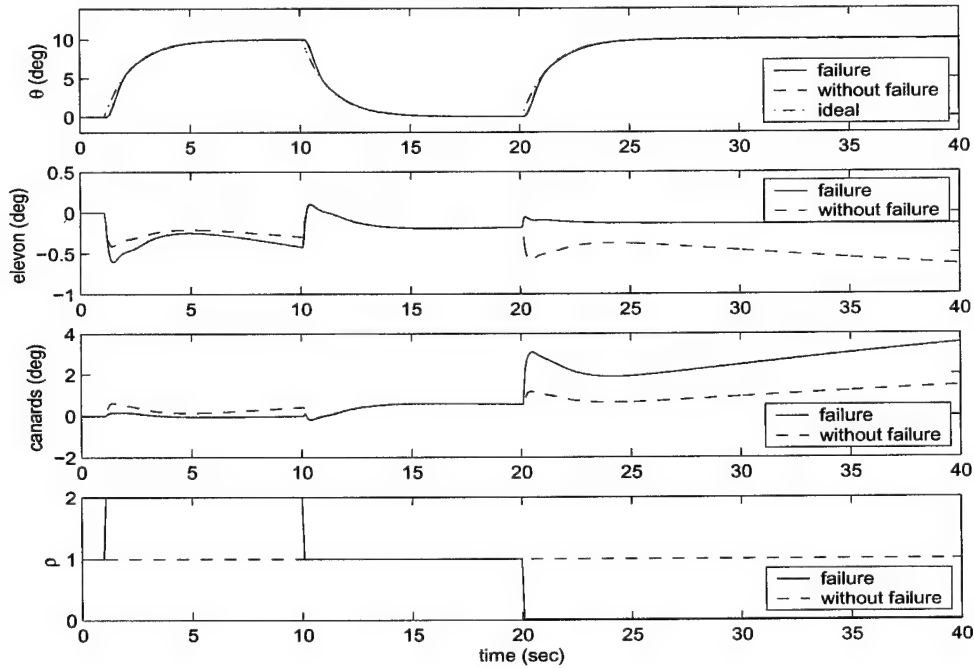


FIG. 5.1. The LPV controller simulations with and without actuator failures.

5. Simulations. In this section, the designed LPV controller is applied to control the HiMAT vehicle for pre-defined failure scenarios. One of the failure scenarios is that a total canard failure occurs 1 and 10 seconds and a total elevon failure occurs between 20 and 40 seconds. The scheduling parameter corresponding to the failure scenario is:

$$\rho = \begin{cases} 0.01, & 1 \leq t < 10 \text{ sec}, \\ 1.00, & 0 \leq t < 1 \text{ sec}, \quad 10 \leq t \leq 20 \text{ sec} \\ 2.00, & 20 < t \leq 40 \text{ sec}. \end{cases} \quad (5.1)$$

For the purpose of comparison, the LPV controller for the HiMAT vehicle is simulated both with and without actuator failures. The simulation results are shown in Figure 5.1. The pitch angle commands are given as 10° at 1 sec, 0° at 10 sec, and 10° at 20 sec, sequentially.

In this simulation, the scheduling parameter corresponding to the true failure parameters, as shown in the bottom of Figure 5.1 is fed into the LPV controller. It is observed that the LPV controller achieves the desired goal of tracking pitch commands in the presence of actuator failures. It can be seen from the second and the third plots in Figure 5.1 that the LPV controller always relies on the healthy actuator to track the pitch commands and abandons the failed actuator. For example, the LPV controller keeps the elevon actuator signals close to zero at the elevon actuator failure case.

The LPV controller is also simulated for the same faulty system as described in equation (5.1) but with bounded real parameter perturbations: $\Delta_p = \text{diag}([\delta_1, \delta_2])$, $\|\Delta_p\| \leq 1$. Two examples of simulations with perturbations are shown in Figure 5.2. "pert1" and "pert2" in Figure 5.2 denote the cases $[\delta_1 \ \delta_2] = [1 \ 1]$ and

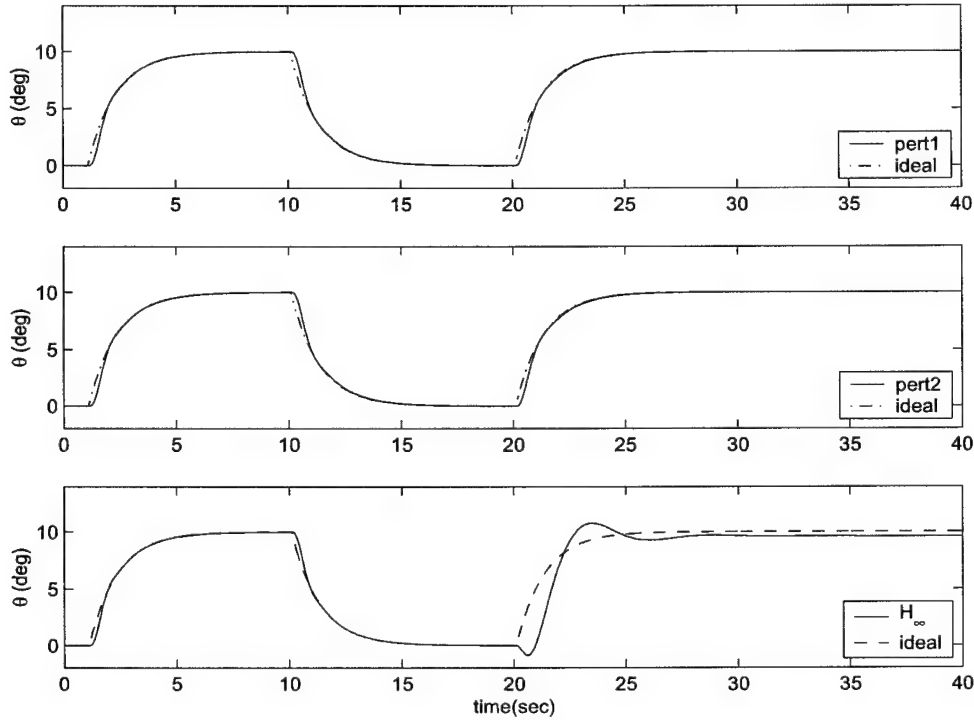


FIG. 5.2. Time responses of pitch angle with LPV and H_∞ controllers.

$[\delta_1 \ \delta_2] = [-1 \ -1]$, respectively. The simulation results show that the LPV controller can robustly stabilize the perturbed system and achieve the desired performance level of tracking the pitch angle commands.

For the purpose of comparison, a fixed H_∞ controller is designed at $\bar{\rho} = 1$ (without failures) using μ -synthesis Toolbox [3] with the same weighting functions described in Section 4. The closed-loop response with this H_∞ controller is also simulated for the actuator failure scenario of equation (5.1), and shown in the

bottom plots of Figure 5.2. It can be seen that the H_∞ controller can achieve the desired performance level when canard fails ($1 \leq t < 10$ sec). The H_∞ controller cannot, however, achieve the desired performance level at the elevon failure. This is consistent with the finding through reconfigurability calculation [10] that the canards are less effective in controlling the pitch movement than elevons, and that loss of elevon effectiveness can significantly affect tracking the pitch commands.

The control signals of the LPV and H_∞ controllers are plotted in Figure 5.3 for the same failure scenario. Since the control signals of the LPV controller are the same with or without perturbations, only simulation

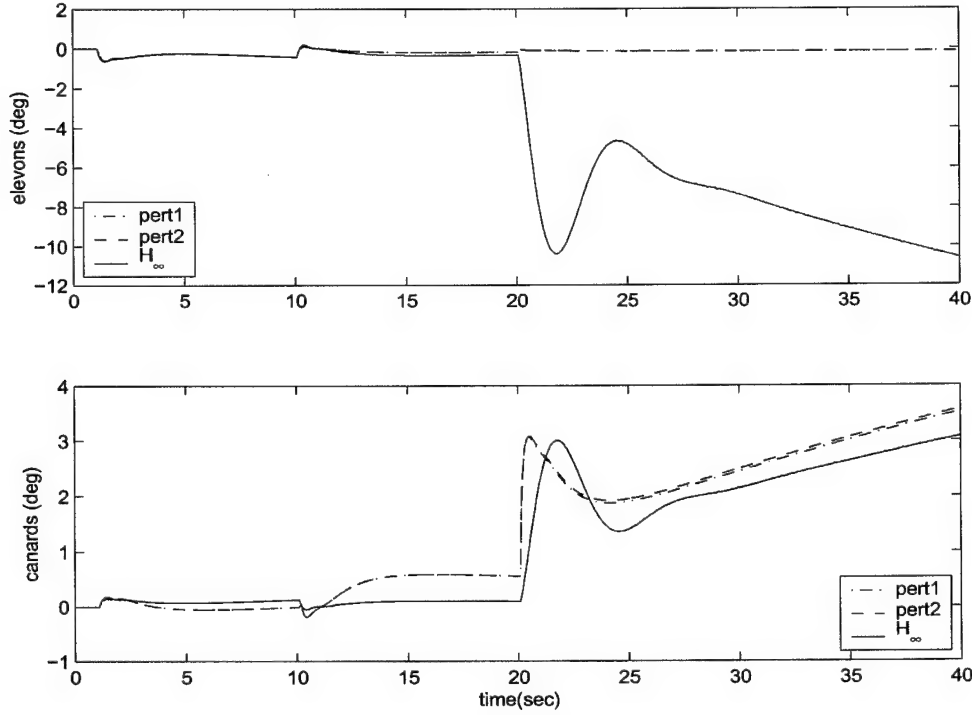


FIG. 5.3. Control signals for each actuator with the LPV and H_∞ controllers.

results with “pert1” and “pert2” are plotted in Figure 5.3. It can be observed from Figure 5.3 that the elevon signals of the H_∞ controller are significant despite the failure of the elevons, while the elevon signals from the LPV controller are insignificant and the canard signals are to compensate the elevon failure in Figure 5.3.

Now, the fault parameters are estimated with an on-line estimator that is integrated into the LPV controller as shown in Figure 5.4. The on-line estimator in Figure 5.4 has two parts: one is a two-stage discrete Kalman filter and the other carries out a simple logic of equation (4.7) that converts the bias estimates to the corresponding scheduling parameter estimate. The following set of parameter values are used in the two-stage Kalman filter. Sampling time is set at 0.01 sec to capture the response details of the open-loop dynamics of the vehicle. The covariance matrices Q_k^x , Q_k^γ and R_k^γ described in Section 3 are set as constant matrices with values:

$$\begin{aligned} Q_k^x &= 3 \text{diag}([1, 0.01^2, 0.01^2, 0.01^2]), \\ Q_k^\gamma &= 3 \text{diag}([0.05^2, 0.05^2]), \\ R_k^\gamma &= 3 \text{diag}([0.01^2, 0.01^2]). \end{aligned}$$

The covariance matrices affect the convergence of the estimator and the noise level considered in the control synthesis in Section 4. The initial values of estimated state $\hat{x}_{0|0}$ and biases $\hat{\gamma}_{0|0}$ are set as $[0 \ 0 \ 0 \ 0]^T$ and $[0 \ 0]^T$. The initial covariance matrices $P_{0|0}^\gamma$ and $\hat{P}_{0|0}^x$ are set at $10I_2$ and $10I_4$. It is found that the estimates

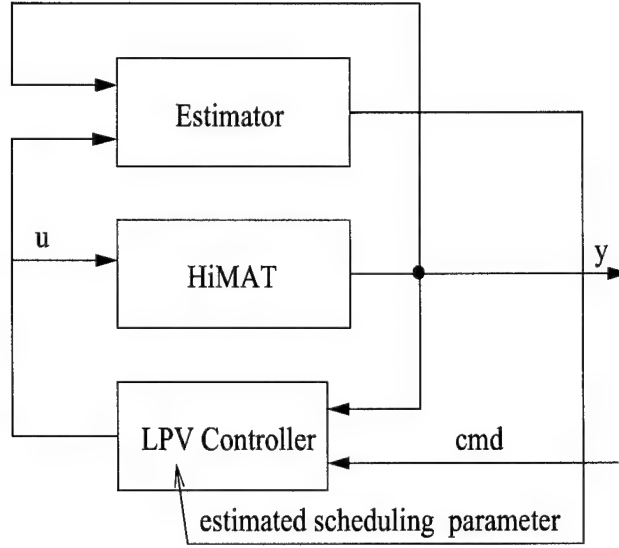


FIG. 5.4. Simulation block diagram of a closed-loop system with an on-line estimator.

TABLE 5.1
Different sets of the varying forgetting factors

Case	λ_0	α_{min}	α_{max}
1	0.90	10	100
2	0.95	10	100
3	1.00	10	100
4	1.00	10^6	10^7

are sensitive to the selection to its initial values, but insensitive to the selection of its initial error covariances.

The most delicate part of the bias estimation lies with the selection of values for λ_0 , α_{min} and α_{max} in equation (3.7). This is done by experiments and with little theoretical guidance. Different sets of values in Table 5 have been attempted. The fault parameter on-line estimate results are shown in Figure 5.5. It is obvious that bias estimation results vary in different cases studied. From the top plots of Figure 5.5, it is noticed that the value of λ_0 affect on convergence rate of estimation. When λ_0 is set as 1 at Case 3, the bias estimate is not convergent at canard failure situation. For this case, the two fault parameter estimates are strongly coupled that can cause false identification of faults. In Cases 1, 2 and 4, initial transients in estimates are visible, since the canards are less effective in controlling pitch angle. It is unknown how the control surface effectiveness is directly related with the transient behavior of the parameter estimator of the two-stage Kalman filter. For Case 4, the covariance matrix P^γ is immediately high value after one step integration since α_{min} is defined as 10^6 . It is founded from the results of Case 4 that the high value of the covariance matrix P_k^γ leads to good estimate of the scheduling parameter.

Simulation results at Case 1 are shown in Figure 5.6. "TV" and "VFF" in Figure 5.6 denote that the LPV controller is evaluated at the true values (TV) of the failure parameters and at the estimated failure parameters with a variable forgetting factor (VFF), respectively. It is important to note that the LPV controller evaluated at the estimated parameter can achieve the desired performance of tracking the pitch commands. The difference in tracking performance between using the estimated parameter and the true parameter is very small at the steady state. The time delay and transient in the estimate has not formalized in the LPV control synthesis process. We currently rely on the robustness of the LPV controller.

The delay, though undesirable, is helpful in satisfying the rate bounds on the scheduling parameter, which is one of the assumptions of the LPV control synthesis methodology. Large delays in fault parameter estimates can be detrimental to the stability of a closed-loop system. This is a subject of future study.

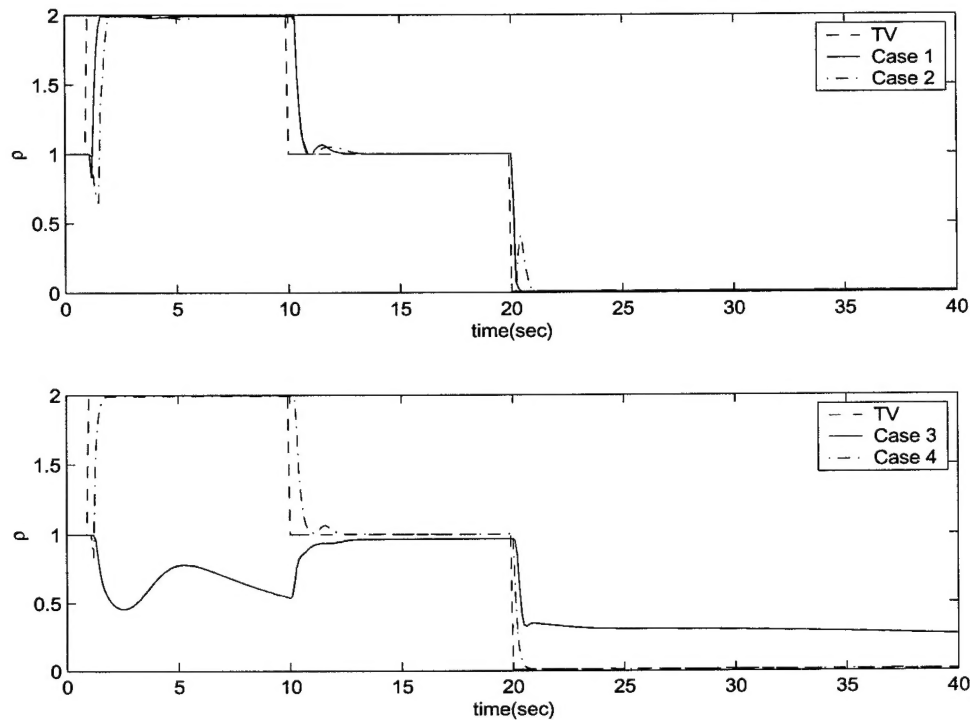


FIG. 5.5. Scheduling parameter estimates for the cases in Table 5.

6. Conclusion. In this paper, the LPV controller is designed based on the estimated scheduling parameter. The system variations due to actuator failures are modeled as functions of estimated parameters and bounded parameter estimation errors. An LPV controller synthesis problem with bounded parameter errors is formulated into two LMI optimizations: one is an LPV control synthesis problem with fixing a scaling factor on a uncertainty block and the other is to find a scaling factor given a control law. The optimization problem is solved by an iteration method. The performance level of the closed-loop system with the designed LPV controller is reduced by the iteration method.

The iteration approach of the LPV synthesis methodology is applied to control of the vehicle at actuator failure cases. It is assumed that the actuators are failed one at a time. Actuator failure parameters of the vehicle are estimated as biases using an augmented Kalman filter. The LPV controller evaluated at the estimated failure parameter is simulated with the plant model which varies as true values of the failure parameter. The simulation results show that the LPV controller achieves the desired performance level of tracking pitch angle commands for actuator failure cases and robustly stabilizes the vehicle.

REFERENCES

- [1] APKARIAN, P. AND ADAMS, R., *Advanced Gain-Scheduling Techniques for Uncertain Systems*, IEEE Transactions on Control Systems Technology, 6 (1998), pp. 21–32.
- [2] APKARIAN, P., GAHINET, P., AND BECKER, G., *Self-scheduled H_∞ Control of Linear Parameter-varying System: a Design Example*, Automatica, 31 (1995), pp. 1251–1261.
- [3] BALAS, G., DOYLE, J., GLOVER, K., AND PACKARD, A., *μ Analysis and Synthesis Toolbox*, The Mathworks, Inc., Natick, MA, 1995.
- [4] BALAS, G., FIALHO, I., PACKARD, A., RENFROW, J., AND MULLANEY, C., *On the Design of LPV Controllers for the F-14 Aircraft Lateral-Directional Axis During Powered Approach*, in Proceedings of the American Control Conference, Albuquerque, NM, 1997, pp. 123–127.

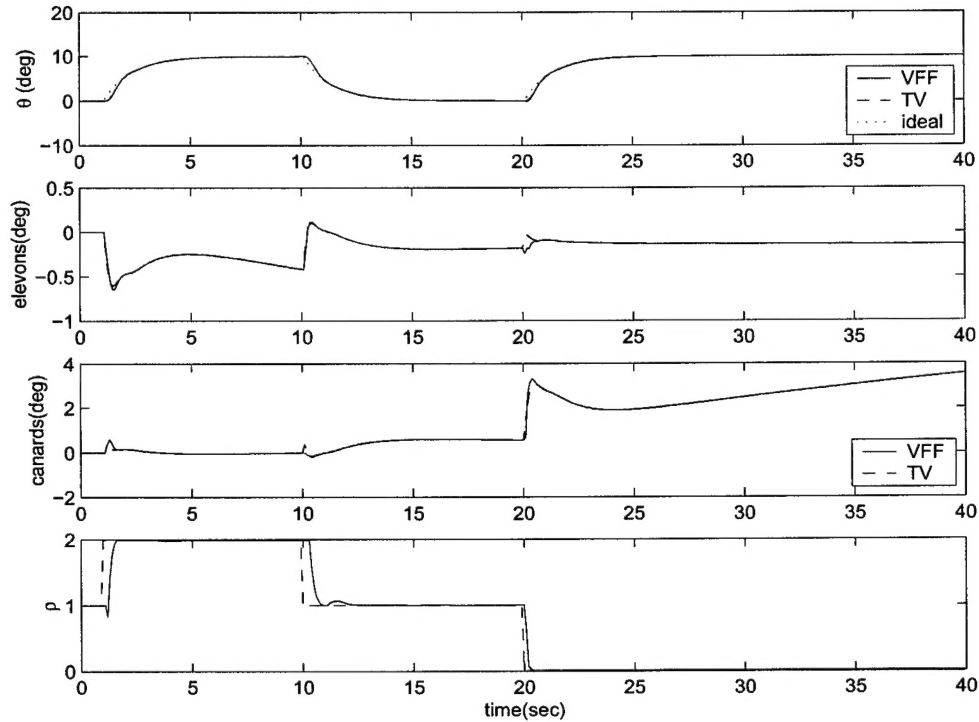


FIG. 5.6. Simulations with the on-line estimator.

- [5] BALAS, G., RYAN, J., SHIN, J.-Y., AND GARRARD, W., *A New Technique for Design of Controllers for Turbofan Engines*, in AIAA 34th Joint Propulsion Conference, Cleveland, OH, 1998, pp. 1-6. AIAA-98-3751.
- [6] BALAS, G., PACKARD, A., RENFROW, J., MULLANEY, C., AND M'CLOSKEY, R., *Control of the F-14 Aircraft Lateral-Directional Axis During Powered Approach*, Journal of Guidance, Control, and Dynamics, 21 (1998), pp. 899-908.
- [7] BECKER, G., *Quadratic Stability and Performance of Linear Parameter Dependent Systems*, PhD thesis, Department of Mechanical Engineering, University of California, Berkeley, 1993.
- [8] KELLER, J. K. AND DAROUACH, M., *Optimal two-stage Kalman filter in the presence of random bias*, Automatica, 33 (1997), pp. 1745-1748.
- [9] N. EVA WU, ZHANG, Y., AND ZHOU, K., *Detection, Estimation, and Accommodation of Loss of Control Effectiveness*, International Journal of Adaptive Control and Signal Processing, 14 (2000), pp. 775-795.
- [10] N. EVA WU, ZHOU, K., AND SALOMAN, G., *Control Reconfigurability of Linear Time-Invariant Systems*, Automatica, 36 (2000), pp. 1767-1771.
- [11] PARKUM, J. E., POULSEN, N. K., AND HOLST, J., *Recursive forgetting algorithms*, International Journal of Control, 55 (1992), pp. 109-128.
- [12] SHAMMA, J., *Gain-Scheduled Missile Autopilot Design Using Linear Parameter Varying Transformations*, Journal of Guidance, Control, and Dynamics, 16 (1993), pp. 256-261.
- [13] SHAMMA, J. AND ATHANS, M., *Guaranteed Properties of Gain Scheduled Control for Linear Parameter-Varying Plants*, Automatica, 35 (1991), pp. 559-564.
- [14] SHIN, J.-Y., *Worst-Case Analysis and Linear Parameter-Varying Gain-Scheduled Control of Aerospace Systems*, PhD thesis, Department of Aerospace Engineering and Mechanics, University of Minnesota, 2000.
- [15] WOŁODKIN, G., BALAS, G., AND GARRARD, W., *Application to Parameter Dependent Robust Control*

Synthesis to Turbofan Engines, in AIAA, Aerospace Sciences Meeting and Exhibit, AIAA-98-0973, Reno, NV, 1998.

- [16] WU, F., *Control of Linear Parameter Varying Systems*, PhD thesis, Department of Mechanical Engineering, University of California, Berkeley, 1995.
- [17] WU, F., PACKARD, A., AND BALAS, G., *LPV Control Design for Pitch-Axis Missile Autopilots*, in Proceedings of the 34th IEEE Conference on Decision and Control, New Orleans, LA, 1995, pp. 188–193.

REPORT DOCUMENTATION PAGE			Form Approved OMB No. 0704-0188	
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188), Washington, DC 20503.				
1. AGENCY USE ONLY (Leave blank)	2. REPORT DATE October 2002	3. REPORT TYPE AND DATES COVERED Contractor Report		
4. TITLE AND SUBTITLE LINEAR PARAMETER VARYING CONTROL FOR ACTUATOR FAILURE		5. FUNDING NUMBERS C NAS1-97046 WU 505-90-52-01		
6. AUTHOR(S) Jong-Yeob Shin, N. Eva Wu, and Christine Belcastro				
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) ICASE Mail Stop 132C NASA Langley Research Center Hampton, VA 23681-2199		8. PERFORMING ORGANIZATION REPORT NUMBER ICASE Report No. 2002-34		
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) National Aeronautics and Space Administration Langley Research Center Hampton, VA 23681-2199		10. SPONSORING/MONITORING AGENCY REPORT NUMBER NASA/CR-2002-211924 ICASE Report No. 2002-34		
11. SUPPLEMENTARY NOTES Langley Technical Monitor: Dennis M. Bushnell Final Report To be submitted to the 2002 AIAA Guidance, Navigation, and Control Conference.				
12a. DISTRIBUTION/AVAILABILITY STATEMENT Unclassified-Unlimited Subject Category 64 Distribution: Nonstandard Availability: NASA-CASI (301) 621-0390		12b. DISTRIBUTION CODE		
13. ABSTRACT (Maximum 200 words) A robust linear parameter varying (LPV) control synthesis is carried out for an HiMAT vehicle subject to loss of control effectiveness. The scheduling parameter is selected to be a function of the estimates of the control effectiveness factors. The estimates are provided on-line by a two-stage Kalman estimator. The inherent conservatism of the LPV design is reducing through the use of a scaling factor on the uncertainty block that represents the estimation errors of the effectiveness factors. Simulations of the controlled system with the on-line estimator show that a superior fault-tolerance can be achieved.				
14. SUBJECT TERMS fault tolerant control system, fault parameter estimation, reconfigurable controller			15. NUMBER OF PAGES 20	
			16. PRICE CODE A03	
17. SECURITY CLASSIFICATION OF REPORT Unclassified	18. SECURITY CLASSIFICATION OF THIS PAGE Unclassified	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT	